Learning Handwriting Features for Parkinson's Disease Diagnosis

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Abstract. Parkinson's Disease (PD) is the second most common neurodegenerative disease, several symptoms are observable through handwriting analysis at an early stage of the disease. Several authors have already used Machine Learning techniques in order to classify PD and Healthy Control (HC) subjects based on expert features extracted from the data. However PD's handwriting impairments are result of numerous symptoms, thus it is very difficult to decide which measure to extract and some inconsistent results have been obtained depending on the handwriting task. Therefore we decided to focus on Deep Learning models which are able to learn features from the raw data.
We present two different model architectures : a Convolutional Neural Network (CNN) and a Hierarchical CNN-Recurrent Neural Network (CNN-RNN). The latter provides encouraging results for end-to-end learning on a small dataset like ours. Pereira et al. had already performed end-to-end learning of handwriting features for PD diagnosis but on another database which we believe is biased because of too young HC. However this is beyond the scope of this paper.
The CNN-RNN outperforms Drotár et al. and Moetesum et al. on some tasks but it is not suited for all. Thus, after majority voting on all tasks, the CNN-RNN still falls below Drotár et al. who use expert features and Moetesum et al. who use transfer learning. For this reason we plan to explore transfer learning in future works.

Keywords: Parkinson's Disease · Deep Learning · end-to-end learning · Handwriting features

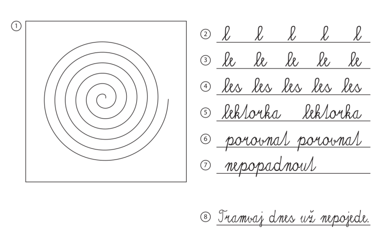

Fig. 1. From [2] : Exam form for the *PaHaW* database

Motivation

Parkinson's Disease (PD) is the second most common neurodegenerative disease [10]. Its diagnosis is considered to be difficult as there is a large number of symptoms which are shared among other diseases (see, e.g. [3]). However, the diagnosis is usually assessed by a neurologist after a physical examination as SPECT and CT scans are costly, invasive, and usually effective when the disease has already progressed to a mature stage [6].

In the description of the disease made by James Parkinson in 1817, writing deficits precede walking deficits. Since then, handwriting has been used to assess PD through tasks like Archimedean spiral or simple subjective rating like in the Unified Parkinson's Disease Rating Scale (UPDRS). Symptoms such as *tremor* or *micrographia* would be visible through a traditional paper-and-pencil examination. However, for a few years, researchers have been arguing that PD *dysgraphia* is larger than *micrographia* and that it is observable through *kinematic* analysis [5]. Moreover, the use of smart pens and digital tablets has allowed for the extraction of a large number of features, thus statistical analysis and machine learning. The goal for the researchers is to provide for a Clinical Decision Support System which would confirm or question the neurologist' diagnosis based on a cheap and non-invasive handwriting exam.

Drotár et al. have gathered data for the *PaHaW* database through the means of a tablet which recorded through the exam the x and y spatial coordinates, a time stamp, the button status which indicates whether the stroke is in-air or on-paper, the pressure and the tilt and elevation which are angles that the pen makes with z and y axis, respectively. In this work we interpret this data as an uni-dimensional image with, thus, 7 channels. The *PaHaW* database comprises 75 subjects (37 PDs and 38 HCs) who all performed 7 tasks, see Fig. 1, except for subject #46 (HC), 60 (PD) and 66 (HC) who did not perform the spiral task and were therefore discarded from this study (as did [6, 4, 7]).

Discussion

The CNN-RNN reaches 73% classification accuracy after majority voting over all tasks and 10-fold cross-validation, thus outperforming the CNN which only reaches 63% classification accuracy. We believe this is because the CNN-RNN has a Hierarchical structure which augments the dataset : each writing sample is split into n strokes and is fed to 2 different convolutional layers depending on if the stroke is in-air or on-paper. It results a sequence of n feature maps which are then fed to the RNN layer. It can also explained because of this separation between in-air and on-paper strokes. This was done after early experiments which suggested that the model extracted the same features from in-air and on-paper strokes although they are very different [1].

Moreover the CNN-RNN outperforms Drotár et al. and Moetesum et al. on the *l*, *le* and *les* tasks. We believe it is because in those tasks, the number of strokes is highly less variable between subjects than in other tasks where our models performs rather poorly. Thus, after majority voting on all tasks, the CNN-RNN still falls below Drotár et al. who achieve 81% classification accuracy using expert features and Moetesum et al. who achieve 83% classification accuracy using transfer learning. For this reason we plan to explore transfer learning in future works.

One major drawback from using Deep Learning is the explainability of the model. Indeed, we can only conjecture from weight visualization which features is our model actually learning in order to diagnose PD. On the contrary, using expert features may provide interesting insights for neurologists. However since Drotár et al. use a Support Vector Machine and extract almost 200 features, their model is not very explainable either.

The biggest challenge of this work was the size of the dataset (72 subjects) which inhibited the generalization capacity of the model : even when using a very small network compared to deep learning standards we still heavily overfit the training set. We expect a great improvement of the results when using a larger dataset. Augmenting the dataset by splitting data into strokes has given interesting results with the CNN-RNN, however classic data augmentation techniques did not provide encouraging results. San Luciano et al. have collected a significantly larger dataset but unfortunately, it is not available publicly and the authors did not respond to our solicitations.

In future works we will explore transfer learning techniques, which have proven to be quite efficient in [6].

Bibliography

[1] Drotar, P., Mekyska, J., Rektorová, I., Masarová, L., Smékal, Z., Faundez-Zanuy, M., 2014. Analysis of in-air movement in handwriting: A novel marker for parkinson's disease. Computer methods and programs in biomedicine 117, 405–411.

[2] Drotár, P., Mekyska, J., Rektorová, I., Masarová, L., Smékal, Z., Faundez-Zanuy, M., 2016. Evaluation of handwriting kinematics and pressure for differential diagnosis of parkinson's disease. Artificial intelligence in Medicine 67, 39–46.

[3] Hughes, A.J., Daniel, S.E., BenShlomo, Y., Lees, A.J., 2002. The accuracy of diagnosis of parkinsonian syndromes in a specialist movement disorder service. Brain 125, 861–870. URL: https://doi.org/10.1093/brain/awf080, doi:https://doi.org/10.1093/brain/awf080, arXiv:http://oup.prod.sis.lan/brain/article-pdf/125/

[4] Impedovo, D., Pirlo, G., Vessio, G., 2018. Dynamic handwriting analysis for supporting earlier parkinsons disease diagnosis. Information 9, 247.

[5] Letanneux, A., Danna, J., Velay, J.L., Viallet, F., Pinto, S., 2014. From micrographia to parkinson's disease dysgraphia. Movement Disorders 29, 1467--1475.

[6] Moetesum, M., Siddiqi, I., Vincent, N., Cloppet, F., 2019. Assessing visual attributes of handwriting for prediction of neurological disordersa case study on parkinsons disease. Pattern Recognition Letters 121, 19--27.

[7] Mucha, J., Mekyska, J., Faundez-Zanuy, M., Lopez-De-Ipina, K., Zvoncak, V., Galaz, Z., Kiska, T., Smekal, Z., Brabenec, L., Rektorova, I., 2018. Advanced parkinson's disease dysgraphia analysis based on fractional derivatives of online handwriting, in: 2018 10th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), IEEE. pp. 1--6.

[8] Pereira, C.R., Pereira, D.R., Rosa, G.H., Albuquerque, V.H., Weber, S.A., Hook, C., Papa, J.P., 2018. Handwritten dynamics assessment through convolutional neural networks: An application to parkinson's disease identification. Artificial intelligence in medicine 87, 67--77.

[9] San Luciano, M., Wang, C., Ortega, R.A., Yu, Q., Boschung, S., Soto-Valencia, J., Bressman, S.B., Lipton, R.B., Pullman, S., Saunders-Pullman, R., 2016. Digitized spiral drawing: A possible biomarker for early parkinsons disease. PloS one 11, e0162799.

[10] Tanner, C.M., Ottman, R., Goldman, S.M., Ellenberg, J., Chan, P., Mayeux, R., Langston, J.W., 1999. Parkinson disease in twins: an etiologic study. Jama 281, 341--346.